UCRL-JRNL-229604

LAWRENCE
LIVERMORE
NATIONAL
LABORATORY

Empirical evidence for a recent slowdown in irrigation-induced cooling

C. Bonfils, D. Lobell

April 2, 2007

Proceedings of the National Academy of Sciences

Disclaimer

Physical Sciences: Geophysics and Environmental Sciences

Empirical evidence for a recent slowdown in irrigation-induced cooling

Céline Bonfils[*†] and David Lobell[‡]

[*]School of Natural Sciences, U.C. Merced, Merced, CA 95344, USA;

[‡]Lawrence Livermore National Laboratory, Livermore, CA 94550, USA

Submitted to Proceedings of the National Academy of Sciences, December 22, 2006

[†]To whom correspondence should be addressed at:
Email: bonfils2@llnl.gov, Phone: (925) 423 9923; Fax (925) 423 4908.

Manuscript information:
18 text pages (including references and figure legends)
5 single column figures: (6.5+11.4+9.1+12.4+14.2)*180 +5*120 = 10248
1 two-column figure: 11.1*360+240= 4236
2 single column tables: (13*60)+2*120 = 1020

Word and character counts:
216 words in abstract
31039 characters in the text (with spaces)
46543 characters in total (including spaces, figures and tables)

Abbreviations footnote: T_{ave}, daily average temperature; T_{min}, daily nighttime minimum temperature; T_{max}, daily daytime maximum temperature; DTR, diurnal temperature range; CIF, current irrigated fraction.

Author contributions: C.B. and D.L. designed research; C.B. and D.L. performed research; C.B. and D.L. analyzed data; and C.B. and D.L. wrote the paper.

Abstract:

Understanding the influence of past land use changes on climate is needed to improve regional projections of future climate change and inform debates about the tradeoffs associated with land use decisions. The effects of rapid expansion of irrigated area in the 20th century has remained unclear relative to other land use changes, such as urbanization, that affected a similar total land area. Using spatial and temporal variations in temperature and irrigation extent observed in California, we show that irrigation expansion has had a large cooling effect on summertime average daily daytime temperatures (-0.15 to -0.25ºC.decade^{-1}), which corresponds to a cooling estimated at -2.0 - -3.3ºC since the introduction of irrigation practice. Irrigation has negligible effects on nighttime temperatures, leading to a net cooling effect of irrigation on climate (-0.06 to -0.19ºC.decade^{-1}). Stabilization of irrigated area has occurred in California since 1980 and is expected in the near future for most irrigated regions. The suppression of past human-induced greenhouse warming by increased irrigation is therefore likely to slow in the future, and a potential decrease in irrigation may even contribute to a more rapid warming. Changes in irrigation alone are not expected to influence broad-scale temperatures, but they may introduce large uncertainties in climate projections for irrigated agricultural regions, which provide roughly 40% of global food production.

Rapid changes in land use, including deforestation, urbanization and irrigation, are widely acknowledged to influence regional scale climate (1-4). Urban areas occupy ~2% of the Earth's land surface (5) and considerable efforts have been devoted to estimating the contribution of urbanization to observed warming in certain regions (6). In contrast, although ~2% of global land surface is irrigated (18% of the 15.4 x 10^6 km^2 of world's agricultural land, 7), the role of irrigation in observed temperature trends has been less a subject of investigation.

Because the surface cooling that accompanies evaporation of irrigation water seems negligible in comparison with global greenhouse warming, and because the positive radiative forcing associated with the increase in water vapor is small (8), influences of irrigation are often ignored in climate projections and often neglected in the process of detecting human-induced climate change (9). Yet, irrigated lands contribute to 40% of global food production and uncertainties in regional climate projections and associated impact on crops depend on the future of irrigated agriculture and the magnitude of climate response to this land-use change (10). Moreover, modeling studies have identified the expansion of irrigation in regions with low rainfall, such as California, as a first-order climate influence (11), the effects of which can attenuate a greenhouse-gas-induced warming (10-12). Alternatively, stabilization or retraction of irrigation practice could accelerate greenhouse warming in agricultural regions.

Previous assessments of irrigation’s impacts on climate, dating to at least 50 years ago (13) and including both modeling and observational studies, have produced conflicting results and provided limited insight into *quantifying* irrigation’s climate effects because of several simplifying assumptions. Some observational studies highlight a contrast between pre- and post-irrigation temperature trends in irrigated regions (14-16), but most do not document the rate at which irrigation evolved, or account for other potential climate forcings. Additional studies have compared temperatures in irrigated and non-irrigated sites, assuming that differences can be attributed to this disturbance (17-20). Part or all of the differences can, however, arise from variations in climate regimes or land characteristics (elevation, latitude, distance from sea, 21) and other external factors (such as urbanization, aerosols or ozone) that can obfuscate the atmospheric signature of irrigation, especially when their spatial patterns correlate with irrigation patterns.

Modeling studies (10-11, 15, 22) show that, among other effects, irrigation causes large reductions in surface daytime temperatures. However, the amplitude of this change, as well as the sign of the change in nighttime temperature often depend on the parameterization adopted to mimic irrigation and the climate model used (11). Moreover, some assumptions such as fixing a high value of soil moisture throughout the growing season, whereas moisture levels in actual irrigated fields are likely lower and more variable in time, can result in overestimating the effects of irrigation on temperatures.

We combined detailed spatial and temporal datasets to quantify the net impact of widespread irrigation on local and regional climate and to better understand recent observational temperature trends in irrigated regions (see Data and Methods). Analyses were first conducted for California, the top irrigating State in the U.S. (3.3 millions hectares), and then for five other widespread irrigated regions of the world (Fig. 1).

Results and Discussion

Observed Irrigation and Temperature Time Series

Since the creation of irrigation districts in 1887, the development of irrigation (Fig. 2*A*) has radically modified the landscape in California, particularly in the previously arid San

Joaquin Central Valley, that is now the mainstay of multi-billon dollar agricultural economy of California. With a rapid expansion in the early decades of the 20^{th} century (1.4 millions hectares in 1935) and a development more moderate until the 1980's (3.2 millions hectares), irrigation is a time-varying climate forcing that we compared with temperature variations from four different datasets (Fig. 2*A*, see Data and Methods). Time-series of temperature differences d(t) were computed by subtracting spatially averaged summer (June-August) T_{min} and T_{max} in a reference area[§] (where current irrigated fraction CIF ranges between 0.1 and 10%) from spatially averaged values over intensively irrigated land (CIF, > 50%). Use of d(t) removed variability common to both time-series (23), isolating the impact of irrigation from those of large-scale forcings.

A very close correspondence is evident between changes in irrigation and d(t) for T_{max} since 1915 (Fig. 2*A*). The temperature changes are gradual and concomitant with irrigation growth. The doubling of irrigated area from 1915 to 1979 was associated with a significant -0.15 – -0.25ºC.decade^{-1} cooling relative to the modestly irrigated reference region (Table 1) or a total of 1.0 – 1.6ºC cooling over the 65 years. Assuming an equivalent amount of cooling associated with irrigation expansion prior to the study period, the total cooling since the introduction of irrigation practice was 2.0 - 3.3ºC. Moreover, the lack of change in irrigation cover (for 1959-1969 and 1978-1982) co-occurred with small d(t) trends, and a recession of irrigation observed in 1982-1987 was associated with a warming of d(t). The large negative correlation ($r < -0.82$, $p < 0.01$)

[§] *Using low-irrigated as opposed to non-irrigated lands to define the reference time-series is motivated by their greater proximity to intensively irrigated lands. Non-irrigated sub-region would otherwise gather the largest urban areas and remote regions likely influenced by different forcings and exposed to a large variety of climate types (coastal areas, Central Valley and Death Valley desert in the case of California).*

suggests an effect of irrigation on T_{max}. Such consistent correlation between irrigation and observed T_{min} variations is not found across the four datasets (Fig. 2*B*).

The fact that irrigation growth and T_{max} are highly significantly correlated does not prove causality, as other factors correlated through time with irrigation extent could also be affecting T_{max}. In the following section, we therefore analyze the influence of irrigation on temperature by focusing on their spatial patterns.

Spatial Dependence of T_{max} trends

To further test and quantify the impact of irrigation, we have repeated the calculation of d(t) using different levels of CIF (0-20%, 20-30%, ..., 90-100%) and computed the trends of d(t) for T_{max} over 1915-1980, the period of irrigation growth (Fig. 3*A*). The trends are always shown relative to that of the reference region. The percent area covered by each CIF class is indicated in Table 2. Using UW dataset, the cooling effect for summertime T_{max} is observed to increase incrementally with irrigation up to 80%. Most trends over intensively irrigated areas are significantly different from those found in the reference region at the 1% level[¶]. These results corroborate the hypothesis that enhanced evaporative cooling associated with an increase of soil moisture (and vegetation cover) causes a decrease in sensible heat flux to warm the surface during daytime. In

[¶] *To assess whether increasing the irrigation level has a significant effect on temperature trends, we need to assess if the temperature trend over low-irrigated areas are significantly different than that over more intensively irrigated areas. To distinguish small trends difference, we employed a statistical significance of trend differences (23). The test consists at computing the least square linear trend d(t) and test the null hypothesis that the trend is not different from zero at 1% significance level, in accounting for data temporal autocorrelation effect (See Supporting Text).*

comparison, we found no clear effect of irrigation fraction on T_{max} over the 1980-2000 period, with no net growth of irrigation (not shown).

Very similar patterns are found when analyzing PRISM, CRU2.0 and CRU2.1 datasets (see Data and Methods), suggesting that results are not qualitatively very sensitive to the choice of the dataset. For the CRU2.0 and CRU2.1 datasets, there is no grid cells falling in the high levels of irrigation and only one falling in the 20-30% CIF class, but T_{max} consistently declines at a faster rate over the most intensively irrigated regions (CIF > 30%). These results further supports the notion that greater irrigated area causes cooling of summertime T_{max}, since other climate forcings were unlikely to vary both temporally and spatially with irrigation. Irrigation practice in California peaks in summer, is significant in spring but is rather sparse during the fall and winter seasons (24). As expected, trends in wintertime T_{max} change modestly and often not significantly with increasing levels of irrigation (Fig. 3*A*).

Spatial Dependence of T_{min}, T_{ave} and DTR trends

Here we analyze the effect of irrigation fraction on T_{min}, T_{ave} and DTR trends, relative to those observed in the reference region (Fig 3*B*-*D*). Using the UW and PRISM datasets, it appears that effects on June-August T_{min} are positive but very small, indicating that the warming in summertime nights occurring in California since 1915 is unlikely the result of irrigation. Analyzes with CRU2.1 dataset corroborate these results. However, CRU2.0 dataset indicates that increasing levels of irrigation are associated with reduction of nighttime temperatures in both summer and winter seasons. These results are questionable (as well as the correlation found between irrigation and T_{min} in Fig 2*B*) since irrigation practice in California is very modest in wintertime (24) and trends in T_{min} should not be sensitive to the level of irrigation during this season (as seen in UW, PRISM and CRU2.1).

In consequence, the net impact of widespread irrigation (in region where CIF > 50%) is a significant cooling in T_{ave} (between -0.06 and -0.19ºC.decade^{-1}) and a significant decline in DTR (-0.13 to -0.20ºC.decade^{-1}) at the 1% level (Table 1). The results show strong consistency across datasets, at least in the sign of those effects. The surplus of energy at the surface to partition into latent and sensible heat fluxes and the active transpiration of plants in daytime can partly explain why the impact of irrigation is asymmetrical at the diurnal timescale (large during the day and minimal at night).

Analyses in other regions

India, China, U.S., and Pakistan contain the largest areas of irrigated land (FAO, Fig. 4*A*) and have all undergone significant expansion of irrigation since 1961 (+1.4 to + 2.9%.yr^{-1} in average). Similarly, irrigated area in the Aral Sea increased by 60% in 20 years (3%.yr^{-1}) after Soviet policy assigned Central Asia the role of raw material supplier in the 1960's. While irrigation slowed in the former Soviet Union after its dissolution (Fig. 4*B*), irrigation development has continued at a slower rate along the Amu Darya and Syr Darya rivers, shrinking the Aral Sea at a concerning rate (25). We evaluated the effect of irrigation on climate for the period 1950-2000 in Nebraska (NE; second to California in irrigated area in the U.S.) using PRISM dataset, and in Eastern China (CH), the Indo-Gangetic Plains in India and Pakistan (IP) and the Aral Sea Basin (AB) using CRU2.1 dataset. We also focus on Thailand (TH), which includes substantial area of intensively (>50% CIF) irrigated land. Thailand experienced a major growth of irrigation in the 1950s (+13%.yr^{-1} during 10 years) and a rapid expansion since 1960 (+4.9%.yr^{-1} in average) (26).

In most regions, similarly to California, a cooling effect in T_{max} is associated with increasing irrigation fraction in the summer season. In Thailand and in Aral Sea basin, where irrigation has developed rapidly, the amplitude of the effect is estimated at -0.129 and -0.077ºC.$decade^{-1}$, respectively ($p < 0.05$). In Nebraska, our results corroborate those of previous work (16, 27) that shows that mean maximum temperatures decreased over time in irrigated agriculture sites and increased over adjacent natural grass sites. Consistent with a previous study (27), we found a significant cooling effect of irrigation from 1950 to 2000 in regions where current irrigation level exceeds 50% (-0.102ºC.$decade^{-1}$, $p < 0.01$) but no cooling effect over the period 1915-1950, i.e. prior the development of irrigation in Nebraska (0.049ºC.$decade^{-1}$, $p>0.5$).

In Pakistan-India and Eastern China, the attribution of the temperature change to irrigation alone is unclear. In these regions, the 1979-1992 average in aerosol optical depth from the Total Ozone Mapping Spectrometer dataset (Nimbus7-TOMS, 28) co-varies with the level of irrigation (Fig. 6). In comparison, the distribution in aerosol is spatially homogeneous over the other regions. By reflecting a fraction of sunlight to space or by absorbing it, aerosols contribute to the observed cooling and obfuscate a change in temperature attributable to irrigation. Aerosols, such as black carbon, might be of particular concern, being largely emitted in rural areas (household burning of biofuels and coal, biomass burning). In India, the decrease of temperature trends with increased CIF in summer (the peak of the agricultural cycle in India) is consistent with the results from California but we cannot determine how much of this cooling is due to irrigation alone. In China, T_{max} responds modestly to the level of irrigation in summer but increases significantly over irrigated soils in winter. A possible explanation for this finding is that a factor whose effects raise T_{max}, such as urbanization, is correlated spatially with irrigation and thus canceled out effects of irrigation in summer. This is likely since most Chinese stations are located in or near cities (6). Additionally, in CRU2.1, the underlying station network is considerably sparser in China than, for example, in the U.S., and this considerably complicates the correction for spatial and temporal inhomogeneities (6). In any case, our methodology appears less suitable for detecting the influence of irrigation over large regions, where other climate forcings can exhibit substantial spatial variability.

The relative importance of irrigation for observed trends in CA

In California, both T_{min} and T_{max} have increased in winter between 1915 and 2000 at a rate exceeding those possible from natural climate variability alone (12). Contributions from external factors, such as increase in greenhouse gases, are thus required to explain such trends. In summer, while T_{min} has increased significantly, there has been no significant trend for T_{max}, results that are not sensitive to the inclusion of adjustments for urbanization effects. The observed worldwide decline in DTR in the latter part of the 20th century is often associated with increase in cloud cover and soil moisture (29-30). In Central Valley, summertime cloudiness is too low to be implicated in explaining differential T_{min} and T_{max} trends. A more credible hypothesis is that irrigation has counteracted a greenhouse-gas-induced warming during the day.

Whether T_{min} trend can be influenced by an irrigation effect or caused by other forcings is an object of controversy (e.g: 11, 20, 31-33). While there is no consensus among modeling studies, two observational studies (33, 20) have reported that irrigation can explain a large increase in T_{min}. In comparing surface temperature trends estimated from reanalyzes with those registered at the weather stations, Kalnay and Cai (33) found rapid increase in T_{min} (and T_{max}) in Central Valley region that they attribute to changes in land-use (including both irrigation and urbanization effect). Based on an apparent contrast in summer T_{min} trends in the Central Valley and the adjacent Sierra mountains, Christy *et al.* (20) attribute the nighttime warming in the Valley to its expanding irrigation over time. Our results (Table 1) do not corroborate this interpretation and reveal, on the contrary, that irrigation cannot explain the large nighttime warming in California.

We explore here the possibility that climate response of irrigation has counteracted that of increasing greenhouse-gases in summer T_{max} in the State of California. We previously estimated that irrigation caused a -0.15 – -0.25ºC.decade^{-1} cooling over the 1915-1979 period in regions of the Central Valley that are in average 75% irrigated. This corresponds to a -0.2 – -0.33ºC.decade^{-1} cooling in regions 100% irrigated. Considering that for the entire State, about 24% the UW grid cells have a CIF above 10% (Table 2), we can estimate that ~11% of California is irrigated at 100%[•]. In consequence, the *regional* effect of irrigation on summer T_{max} trends is of -0.022 – -0.037°C.decade^{-1}, which is smaller in magnitude than the observed trend for the State (-0.048±0.06°C.decade^{-1}, from UW), and thus insufficient to entirely explain the summer T_{max} cooling between 1915 and 1979. However, this effect is probably underestimated: our analysis totally ignored the fact that meteorological stations in irrigated areas may influence the interpolated temperatures for non-irrigated cells in the gridded datasets, and that the regions of reference from which are computed our trends may also be cooler than they would have been without the presence of irrigation. Indeed, it has been shown that,

[•] *11% is obtained in summing the product, for each class, of its mean CIF (5%, 15%, 25%, etc…) and its irrigation fraction (Table 2).*

through advection of moisture from evapotranspiration and cloudiness feedbacks, effects of irrigation are probably not limited to regions of direct forcing but can impact broader-scale climate (18, 22), up to 75km away (11). Accounting for such effects would involve trend analyses comparing UW dataset and a new version of UW dataset, in which effects of irrigation would be adjusted at the station level.

Since its introduction, we estimated that the local impact of irrigation has been of 2.0 - 3.3ºC in regions that are on average 75% irrigated, which roughly corresponds to a 2.7 – 4.4ºC cooling for a total conversion from potential to irrigated land. These values are smaller than those inferred from modeling studies (4.7 – 8.2ºC, 11). This could be attributed to the limits of our method, but also to the fact that soil moisture depends on irrigation technique and crop. While flood irrigation was practiced on more than 80% of irrigated land in California prior to 1970, sprinkler and drip irrigation systems are now more widely used to optimize water use and yield production (34). In consequence, observed soil moisture is likely often well below values assumed in models, such as field capacity.

Current and future evolution of irrigation

Our results suggest that the rate at which irrigation developed rather than the presence of irrigation is at the origin of net cooling effect. In California, the end of irrigation expansion since 1980 is likely to persist in the future, as urban areas and water demand continue to expand (35). A recession in irrigation would result in substantial warming in the Central Valley. In most other intensively irrigated regions of the world, such as Asia, growth in irrigation has recently decelerated and is projected to slow even more in the future (36). In the U.S., with less irrigated farms, irrigation has recessed for the first time by 2% between 1998 and 2003. Throughout the major irrigation regions of the world, the cooling influence of irrigation on Tmax, which has suppressed warming from other climate forcings such as increased CO_2, will likely be much smaller in the next 50 years than in the past century.

Data and methods

Irrigation datasets: Time-series of irrigated area in California were documented from 20 U.S. Department of Agriculture censuses available since 1889 and linearly interpolated between available censuses. Spatial variations in irrigation extent were provided by a high-resolution (5' x 5') gridded dataset of current irrigation fraction (CIF, in percent, Fig. 1) (37).

Temperature datasets: Spatial and temporal climate variations in daily average (T_{ave}), nighttime minimum (T_{min}) and daytime maximum temperatures (T_{max}) and in diurnal temperature range (DTR= T_{max} – T_{min}) over California are documented by four observational gridded datasets (UW, PRISM, CRU2.0 and CRU2.1) for the 1915-2000 period (the longest common period covered by the datasets). All observational products include some form of adjustment for non-climatic influences (*e.g.*, changes in instrumentation, observation time and station location) and are suitable for long-term trend analysis. With a good station coverage over California (including both U.S. Historical Climatology Network (HCN) and Cooperative network observations (COOP)), a high 1/8° x 1/8° resolution and adjustment for urbanization effects, UW dataset (38) represents our best candidate to study the contribution of irrigation to temperature variations in California. PRISM is also a high quality, high resolution and topographically sensitive (4km * 4km) dataset for the United States, based on HCN and COOP stations but also on SNOTEL and agricultural climate data (39). CRU2.0 (40) and CRU2.1 (41) datasets have 1/2° x 1/2° resolution, mainly rely for California on adjusted HCN records and were not adjusted for urbanization effects. However, their addition allowed the robustness of results to observational uncertainty over California to be tested. In addition, the CRU datasets enabled analyses in other regions that are not documented by the UW or the PRISM dataset. Trends in T_{min}, T_{max} and T_{ave} from UW and CRU datasets agree well with those computed from individual USHCN stations data in California for all seasons (12).

Regridding and elevation criterion: In all analyses, irrigation and elevation datasets are regridded to the resolution of each temperature dataset and all calculations are executed after masking data that do not represent California. To avoid any climate bias generated by elevation, our study focused only on irrigated and non-irrigated areas located in low elevation: any grid cells above 500 meters of altitude were excluded from analysis.

Acknowledgments

CB was supported by the State of California through the Public Interest Energy Research Program, and DL by a Lawrence Fellowship from LLNL under Contract W-7405-Eng-48. Datasets were provided by the Surface Water Modeling group at the University of Washington via the web site at http://www.hydro.washington.edu/Lettenmaier/gridded_data), by the Climatic Research Unit (CRUTS2.0, CRUTS2.1, http://www.cru.uea.ac.uk/cru/data/) and by the PRISM Group, Oregon State University (http://www.prismclimate.org). We warmly thank P. Duffy and B. Santer for their constructive comments. DL work was performed under the auspices of the U.S. Department of Energy by University of California, Lawrence Livermore National Laboratory under Contract W-7405-Eng-48.

References

1. Baede APM *et al.* (2001) in *Climate Change 2001: The Scientific Basis*, eds Houghton JT *et al.* (Cambridge Univ Press, Cambridge, UK), pp 85-98.
2. Feddema JJ, Oleson KW, Bonan GB, Mearns LO, Buja LE, Meehl GA, Washington WM (2005) *Science* 310:1674-1678.
3. Foley JA, DeFries R, Asner GP, Barford C, Bonan G, Carpenter SR, Chapin FS, Coe MT, Daily GC, Gibbs HK, Helkowski JH, Holloway T, Howard EA, Kucharik CJ, Monfreda C, Patz JA, Prentice IC, Ramankutty N, Snyder PK (2005) *Science* 309:570-574.
4. Govindasamy B, Duffy PB, Caldeira (2001) *Geophys Res Lett* 28:291-294.
5. Grübler A (1994) in *Changes in Land Use and Land Cover: A Global Perspective*, eds Meyer WB, Turner BL II (Cambridge Univ Press, Cambridge, UK), pp 287-328.
6. Zhou, L, Dickinson RE, Tian Y, Fang J, Li Q, Kaufmann RK, Tucker CJ, Myneni RB (2004) *Proc Nat Acad Sci* 101:9540-9544.
7. Food and agriculture organization of the United Nations FAOSTAT http://faostat.fao.org/.
8. Boucher O, Myhre G, Myhre A (2004) *Clim Dyn* 22:579-563.
9. Pielke RA Sr (2005) *Science* 310:1625-1626.
10. Lobell, DB, Bala G, Bonfils C, Duffy PB (2006) *Geophys Res Lett* 33:L13709, 10.1029/2006GL026770.
11. Kueppers, LM, Snyder MA, Sloan LC, Cayan D, Jin J, Kanamaru H, Kanamitsu M, Miller NL, Tyree M, Du H, Weare B (2006) *Glob Planet Change* revised.
12. Bonfils, C, Duffy P, Santer B, Lobell D, Phillips, Wigley TML, Doutriaux C (2006a) *Climatic Change* revised.
13. de Vries DA (1959) *J Meteorol* 16:256-270.
14. Fowler WB, Helvey JB (1974) *Science* 184:121-127.
15. Adegoke, JO, Pielke RA, Eastman J, Mahmood R, Hubbard KG (2003) *Month Weath Rev* 131:556-564.
16. Mahmood, R, Hubbard KG, Carlson C (2004) *Int J Climatol* 24:311-327.
17. Segal M, Pan Z, Turner RW, Takle ES (1998) *J Appl Meteorol* 37: 325-331.
18. Burman RD, Wright JL, Jensen ME (1975) *Trans. ASAE* 18:1089-1093.
19. Idso, SB, Reginato, RJ, Reicosky, DC, Hatfield, JL (1981) *Agron J* 73:826-830.

20. Christy JR, Norris WB, Redmond K, Gallo KP (2006) *J Clim* 19:548-563.

21. Geerts B (2002) *Theor Appl Climatol* 72:157-163.

22. Chase, TN, Pielke RA, Kittel TGF, Baron JS, Stohlgren TJ (1999) *J Geophys Res-Atm* 104:16673-16690.

23. Santer BD, Wigley TML, Boyle JS, Gaffen DJ, Hnilo JJ, Nychka D, Parker DE, Taylor KE (2000) *J Geophys Res* 105:7337-7356.

24. Salas W, Green P, Frolking S, Li C, Boles S (2006) in *Estimating Irrigation Water Use for California Agriculture: 1950s to Present*, California Energy Commission, 33 pp.

25. Small EE, Sloan LC, Nychka D (2001) *J Clim* 14:284-299.

26. Federal Research Division of the Library of Congress, Thailand: A Country Study http://countrystudies.us/thailand/.

27. Mahmood, R, Foster SA, Keeling T, Hubbard KG, Carlson C, Leeper R (2006) *Glob Planet Change* 54:1-18.

28. Torres, O, Bhartia PK, Herman JR, Sinyuk A, Ginoux P, Holben B (2002) *J Atmos Sci* 59:398-413.

29. Dai A, Genio AD Del, Fung IY (1997) *Nature* 386:665-666.

30. Trenberth KE (2004) *Nature* 427:213.

31. Bonfils C, Duffy PB, Lobell DB (2006) *J Clim* revised.

32. Lobell DB, Bonfils C (2006) *J Clim* in review.

33. Kalnay E, Cai, M (2003) *Nature* 423:528-531.

34. Orang MN, Snyder RL, Matyac JS (2005) in California Water Plan Update 2005 (department of Water Resources, Sacramento) 4:300-317.

35. National Research Council, “A New Era for Irrigation” (Natl Acad Sci, 1996).

36. J Bruinsma, Ed, World Agriculture: Towards 2015/2030: an FAO Study (Earthscan, 2003).

37. Döll P, Siebert S (2000) *Icid J* 49:55-66.

38. Hamlet, AF, Lettenmaier DP (2005) *J Hydrometeorology* 6:330-336.

39. Daly C, Neilson RP, Phillips DL (1994) *J Appl Meteor* 33:140-158.

40. Mitchell, T D, Carter TR, Jones PD, Hulme M, New M (2004) Tyndall Working Paper 55 (Tyndall Centre, UEA, Norwich, UK) http://www.tyndall.ac.uk/.

41. Mitchell TD, Jones PD (2005) *Int J Climatol* 25:693-712.

Figure legends

Figure 1: Global map of the fraction of each 5’ x 5’ grid cell equipped for irrigation (37). Circles indicate major irrigation regions used in this study.

Figure 2: Observed time-series of irrigated land cover in California and June-August temperature differences between intensively irrigated lands (CIF > 50%) and a reference area (0.1-10% CIF), both located in the Central Valley region (CV: 118.25-126.25ºW, 34.75- 40.25ºN). T_{max} (A) and T_{min} (B) time-series are estimated using UW (red), PRISM (green), CRU2.1 (blue) and CRU2.0 (brown) data below 500m of elevation. Unfiltered (pale dotted lines) and 11-year running averages (bright solid lines) are shown, both with climatology subtracted for clarity. Irrigation time-series (black line, right, vertical scale is reversed) is interpolated from data collected in USDA censuses (represented by black dots). Numbers in panel show correlation coefficients between irrigation and each temperature time-series.

Figure 3: Observed 1915-1979 trends in June-August (green) and December-February (blue) T_{max} (*A*) in regions of the Central Valley partitioned by CIF classes, relative to the trend in the reference class. Close circles indicate that trend of d(t) are statistically significant at $p < 0.01$. The same analyses were conducted for T_{min} (*B*), T_{ave} (*C*) and DTR (*D*).

Figure 4: Irrigated area expressed in 10^6 Ha (*A*) and in percent relative to 1961 (*B*) for six different regions of the World.

Figure 5: Observed 1950-2000 June-August and December-February T_{max} trends in regions partitioned by CIF classes, relative to a reference class (0.1-10% CIF) for five irrigated regions, using the PRISM dataset for the Nebraska (NE) region and CRU2.1 for the four other regions.

Figure 6: Observed 1979-1992 June-August and December-February average in aerosol optical depth (AOD) from the Total Ozone Mapping Spectrometer dataset (Nimbus7-TOMS, 28) in six regions partitioned by CIF classes.

Table 1:

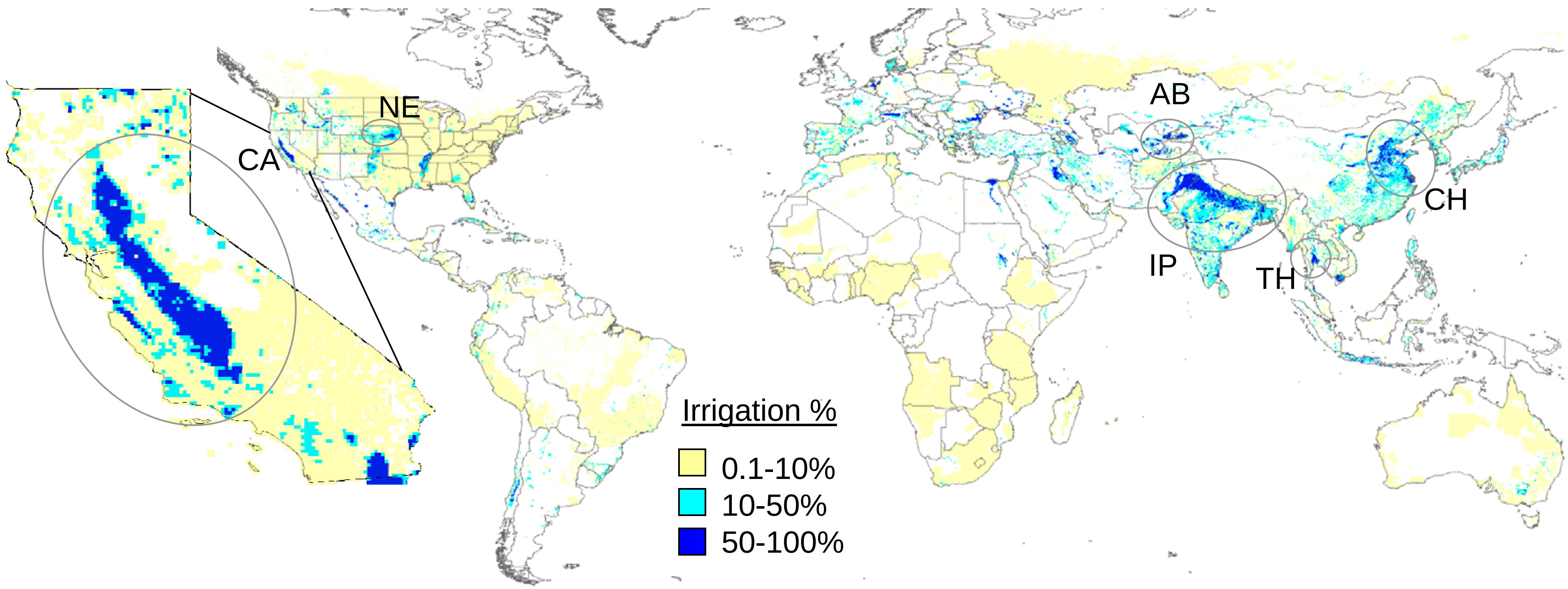
Climate least-squares linear trends (in ºC.decade^{-1}) for 1915-1979 in heavily irrigated areas of the Central Valley (CIF > 50%) relative to the modestly irrigated reference region (CIF between 0.1 and 10%). The 2σ trend confidence intervals are adjusted for temporal autocorrelation effects (See Supporting Text). Asterisks indicate significance levels: 0.01 (***), 0.05 (**) and 0.1 (*).

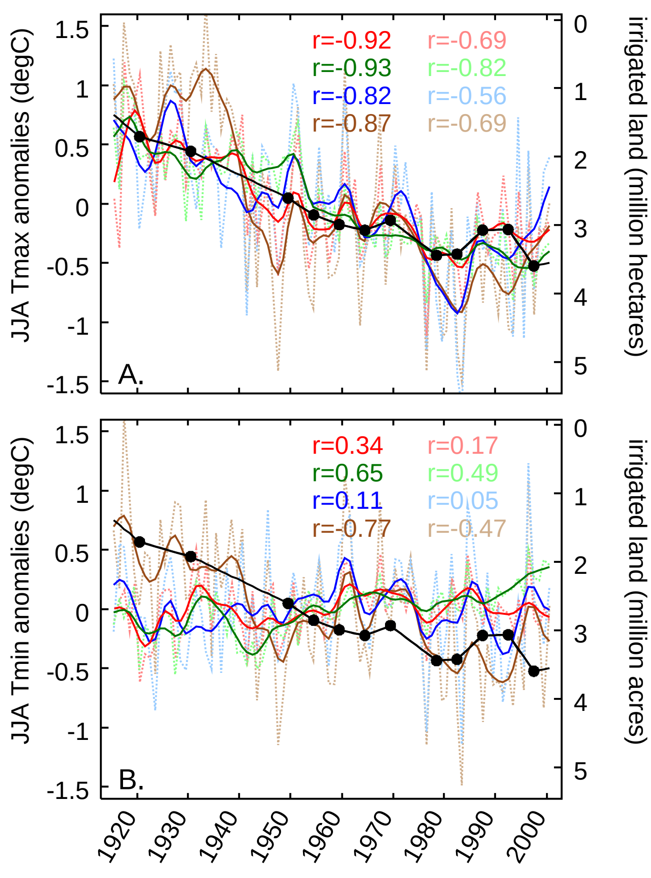
CIF > 50%	Tmax	Tmin	Tave	DTR
UW	-0.153 ± 0.049***	+0.024 ± 0.038	-0.064 ± 0.033***	-0.176 ± 0.056***
PRISM	-0.164 ± 0.035***	+0.038 ± 0.037*	-0.063 ± 0.020***	-0.202 ± 0.062***
CRU2.1	-0.157 ± 0.065***	+0.018 ± 0.059	-0.070 ± 0.055**	-0.176 ± 0.059***
CRU2.0	-0.249 ± 0.099***	-0.122 ± 0.079***	-0.186 ± 0.084***	-0.128 ± 0.066***

Table 2:

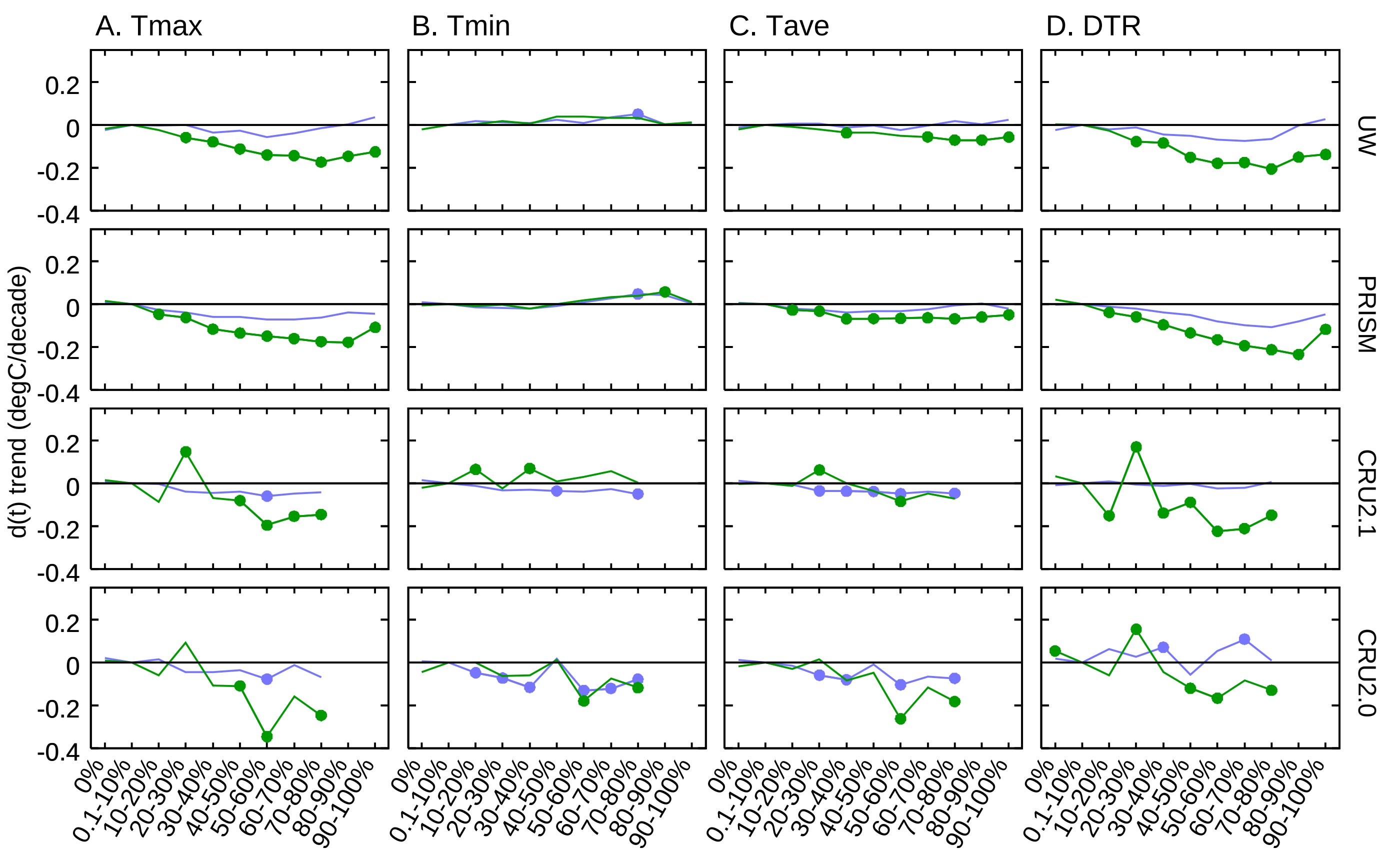
Distribution of irrigated areas in the studied region (focused on Central Valley - CV) and in the entire State of California (in % of total grid cells). For the studied region, the masked areas represent the regions above 500m of elevation and the class (0.1-10%) represents the region of reference.

		Mask	0%	0.1-10%	10-20%	20-30%	30-40%	40-50%	50-60%	60-70%	70-80%	80-90%	90-100%
	UW	45.0	12.2	12.2	4.9	3.6	2.6	2.6	2.2	3.5	5.3	5.0	0.9
CV	PRISM	47.9	13.4	9.5	4.4	2. 9	2.5	2.3	2.2	3.3	5.6	5.1	1.5
	CRUs	51.0	5.2	11.5	8.3	1.0	6.3	6.3	2.1	2.1	6.3	0.0	0.0
	UW	0.0	53.0	23.0	6.9	3.6	2.3	1.9	1.3	1.9	2.8	2.6	0.8
CA	PRISM	0.0	61.1	17.4	5.5	3.1	2.0	1.6	1.3	1.8	2.6	2.6	0.9
	CRUs	0.0	33.3	36.1	13.9	2.2	4.4	3.3	2.2	1.1	3.3	0.0	0.0

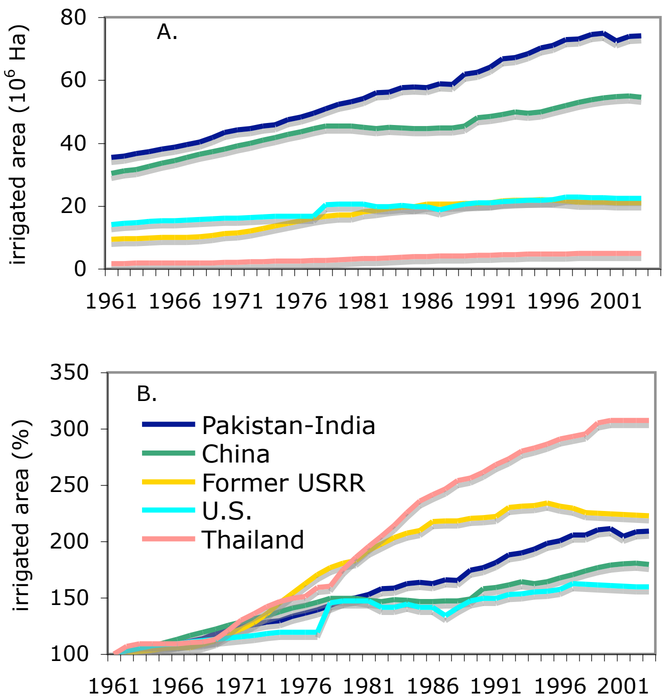

NE
CA
AB
CH
IP
TH
Irrigation %
0.1-10%
10-50%
50-100%

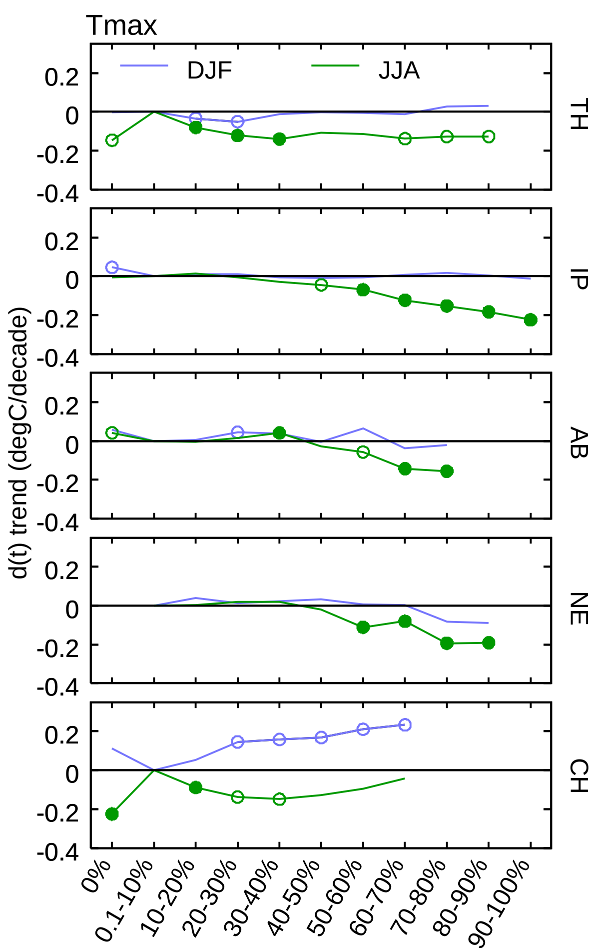


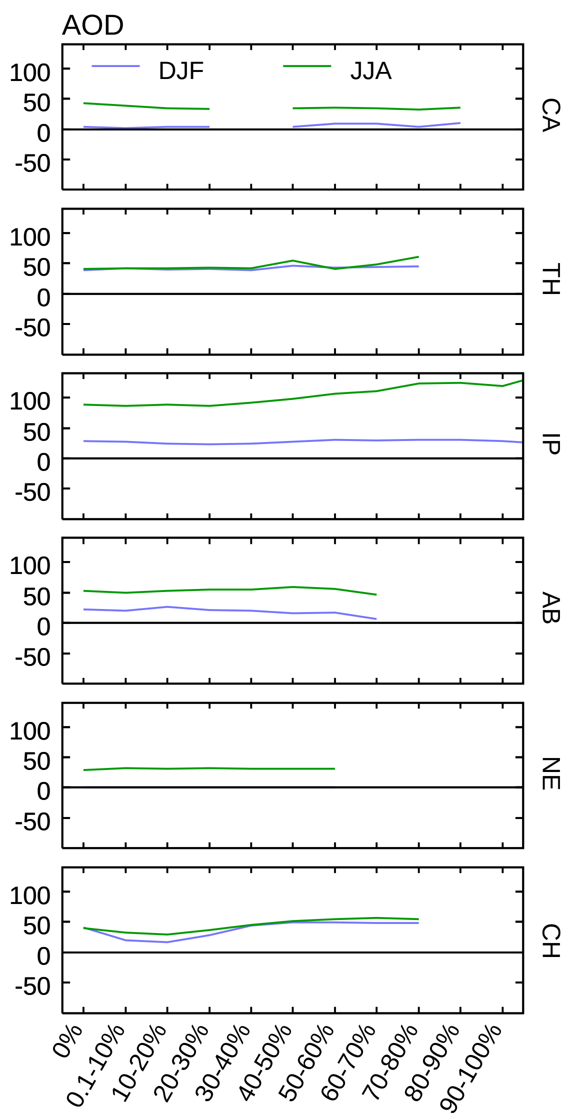
JJA Tmax anomalies (degC)
irrigated land (million hectares)
r=-0.92
r=-0.69
r=-0.93
r=-0.82
r=-0.82
r=-0.56
r=-0.87
r=-0.69
A.
JJA Tmin anomalies (degC)
irrigated land (million acres)
r=0.34
r=0.17
r=0.65
r=0.49
r=0.11
r=0.05
r=-0.77
r=-0.47
B.
1920
1930
1940
1950
1960
1970
1980
1990
2000



A. Tmax
B. Tmin
C. Tave
D. DTR
UW
PRISM
CRU2.1
CRU2.0
d(t) trend (degC/decade)
0.2
0
-0.2
-0.4
0%
0.1-10%
10-20%
20-30%
30-40%
40-50%
50-60%
60-70%
70-80%
80-90%
90-100%


A.
irrigated area (10^6 Ha)
80
60
40
20
0
1961 1966 1971 1976 1981 1986 1991 1996 2001
B.
irrigated area (%)
350
300
250
200
150
100
Pakistan-India
China
Former USRR
U.S.
Thailand
1961 1966 1971 1976 1981 1986 1991 1996 2001


Tmax
DJF
JJA
TH
IP
AB
NE
CH
d(t) trend (degC/decade)
0.2
0
-0.2
-0.4
0%
0.1-10%
10-20%
20-30%
30-40%
40-50%
50-60%
60-70%
70-80%
80-90%
90-100%



AOD
DJF
JJA
100
50
0
-50
CA
TH
IP
AB
NE
CH
0%
0.1-10%
10-20%
20-30%
30-40%
40-50%
50-60%
60-70%
70-80%
80-90%
90-100%